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A qualitative assessment of the use of artificial intelligence in public sector health organisations in Ontario, Canada

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Summary

BACKGROUND: Advancements in artificial intelligence (AI) and machine learning (ML) capabilities and increased access to methods have enabled population-level analysis for research and health system monitoring. However, governments and public authorities may not be aware of the full range of applications, opportunities, and barriers and challenges. The purpose of the present study was to understand the barriers and facilitators of AI/ML and whether (and how) AI/ML was being used (or could be used) in public sector health organisations in a publicly funded health system.

METHODS: Thirteen key informant interviews at three public sector health organisations were conducted. Common themes were identified. An in-person workshop was held in Toronto on 15 May 2024. We identified barriers and enablers and make recommendations for advancing AI/ML in the broader public sector.

RESULTS: A total of six barriers were identified by participants: 1) knowledge, education and expertise; 2) privacy, ethics and security; 3) technology and infrastructure; 4) financial barriers; 5) competing priorities; and 6) fear of being replaced. Key enablers include 1) partnerships; 2) buy-in and support from senior leadership; 3) management and operational supports; and 4) actionable use cases. One prominent use case objective was to enhance healthcare system efficiency, including automating routine or unskilled operations to allow healthcare professionals to focus on higher-value tasks.

CONCLUSION: Demonstrating success from focused small-scale AI applications, partnering with academia, and engaging senior leadership may build confidence and capability, but it is important to share knowledge, experiences, and measure success for the perspectives of different partners.

Introduction

Recent advances in intelligent agents, entities that can react autonomously based on inputs from their environment, have resulted in widespread adoption of such agents in the private sector [1]. In the public health sector, there is increasing recognition of the need to keep pace with the evolution of data analytics, and this includes machine learning (ML) and artificial intelligence (AI) [2]. Unlike private sector organisations, public health agencies are more risk-averse and a publicly funded healthcare system is not subjected to the same financial opportunities or pressures as for-profit institutions are.

Regardless of jurisdiction, public sector health organisations strive to improve the health of populations through a wide range of interrelated activities, including disease surveillance; forecasting; health technology assessment; public education; preventive measures for risk reduction; and health and human resource allocation [3]. With such breadth, there are a range of applications for AI/ML that may overlap from one public health organisation to the next. Whether such methods of-

fer advantages (or not) compared with traditional methods grounded in epidemiology, health economics, operations research, qualitative synthesis, and other disciplines remains to be seen. However, governments and public authorities may not be aware of the full range of AI/ML applications, opportunities, risks, as well as barriers and challenges, and the literature is limited on this topic.

The purpose of this study was to understand the barriers and enablers of AI/ML in public sector health organisations in a publicly funded health system. Following key informant interviews, we identified whether (and how) AI/ML was being used (or would like to be used) and make recommendations for advancing AI/ML in the public sector.

Methods

Definitions

For the present study, we use the term artificial intelligence and machine learning (AI/ML) broadly. Prior to conducting the interviews, we defined AI/ML as an area of study traditionally within the field of computer science dedicated to solving problems commonly associated with human intelligence, such as learning, problem solving, visual perception, and speech and pattern recognition [4]. AI in public health is the application of these techniques to improve disease surveillance, diagnosis, treatment personalisation, resource allocation and healthcare policy.

Setting

This study was conducted from the perspective of public sector health organisations in Ontario, Canada's most populous province. In Canada, healthcare is provisioned under a single-payer system, and despite national alignment, healthcare is managed at the provincial level. The Ontario Ministry of Health oversees funding and operations of healthcare and public health in the province. In scope of the present study, we chose organisations that reflect different public sector health organisations and conducted key informant interviews with mid-to-senior-level staff and management at Ontario Health, Public Health Ontario and Toronto Public Health.

Ontario Health oversees healthcare planning and coordination across the province, including cancer care, kidney disease, mental health and addiction, organ and tissue donation, and palliative care, delivered across a range of settings including primary care, acute care, long-term care and community services. Ontario Health does not provide clinical services. Public Health Ontario provides scientific evidence and expert guidance on chronic disease prevention, infection control and diseases of public health significance without providing direct clinical services. Toronto Public Health is responsible for preventing the spread of disease, promoting healthy living and advocating for conditions that improve health for residents of Toronto, Ontario's most populous city. Toronto Public Health provides clinical services focusing on specific health needs like breastfeeding, dentistry, immunisation, sexual health, drug use and harm-reduction supplies.

Ethics and privacy

The present study was approved by the University of Toronto Research Ethics Board (#45652). Interviewees and the organisations they work at will be kept anonymous if not already in the public domain. Any quotations provided in this report were edited for clarity or to ensure anonymity. All opinions are those of the individual and do not necessarily reflect those of their organisation. We follow the Standards for Reporting Qualitative Research (appendix 2) [5].

Key informant interviews and synthesis

Key informant interviews were performed between January 2024 and March 2024. Oral interviews were conducted on a virtual platform (Microsoft Teams) by epidemiologists/methodologists who have worked in the public sector for a total of 25 years, having experience in data analytics, health policy and data-informed decision-making in the public sector. Key informants were identified a priori by interviewers based on institutional knowledge of who would be good candidates as key opinion leaders on the topic of AI/ML in their respective organisations. Interviewees were asked to provide contacts of their peers who may be able to provide additional insights (snowballing approach). This was continued until data saturation was believed to have been achieved, while considering the time investments required to conduct further interviews [6]. The general script used to guide our interviews is provided in appendix 1; briefly, it covered the following topics:

– The participant's role in the organisation (e.g. whether they or their direct reports work with data; the nature of the work they/their team does; infrastructure related to analytics);

– Any completed, ongoing or planned work using machine learning;
– Whether there is a desire for machine learning in specific areas (e.g. potential use cases);
– Barriers and enablers to implementing a machine-learning solution.

Interviews were conducted, recorded and transcribed using Microsoft Teams. Audio recordings were extracted from the recordings and saved to allow clarification of transcripts if necessary. Each transcript was imported into NVivo14 for coding into themes independently by two investigators (split between SH, TB and JH).

Synthesis followed the post-positivist research paradigm, and we acknowledge that the preconceived notions of the research team are implicitly embedded within the analysis [7]. Coding was both theory-driven (e.g. a result of the subject-matter expertise of the research team; some high-level codes like "enablers" and "barriers" were pre-determined) and data-driven (e.g. researchers created more-specific codes like "financial barriers" or new codes as necessary while reviewing the transcripts) [8,9]. Codes were compiled into themes based on their perceived commonalities, organisational hierarchies and pragmatism, supported using representative quotes.

Intercoder reliability was assessed with percent agreement [10]. First, the transcripts were chunked out into sentences or blocks of sentences reflecting the same stream of thought. This was done because of transcription quality (e.g. pauses in the audio were transcribed into periods and therefore new sentences); interviewee style (e.g. more-elaborate responses with examples would produce more words that can affect character or word overlap rates); idiosyncrasies of individual coders (e.g. one may code a single word from a sentence, while another may have coded the entire sentence to capture the context); and transcript content (e.g. interviewer questions were included). These issues would yield inter-coder reliability statistics unreflective of the actual agreement [10]. We consider a percent agreement >70% to be acceptable [11].

Themes are presented and mapped to the AI Maturity Framework published by Element AI, which classifies an enterprise according to five levels of maturity (exploring > experimenting > formalising > optimising > transforming) across five dimensions (strategy, data, technology, people, governance) [12]. Specific to the public sector, the IBM Center for the Business of Government has released their own framework with six elements divided into technical elements (big data; AI systems; analytical capacity) and organisation elements (innovative climate; governance and ethical frameworks; and strategic visioning) [13].

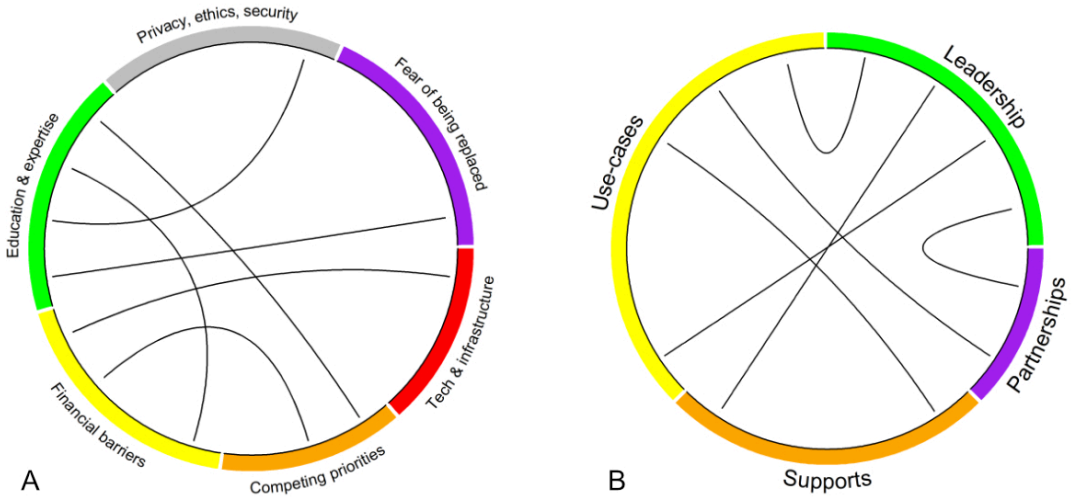
In-person workshop

An in-person workshop was held in Toronto on 15 May 2024. Participation was open to the public, but word-of-mouth invitations were extended to the research team's peers. Participants did not consent to the collection of their sociodemographic data for reporting, but were from a wide range of roles, including graduate students, managers, directors, scientists and Associate Medical Officers of Health. Following a presentation of the themes identified from the key informant interviews (see results below), attendees were asked to think about, discuss with the other participants seated at their table, and report on a set of questions on "How to build data science functionality in public sector organisations". A thematic analysis of responses to these questions was not conducted, but the group discussions offered a venue to supplement the findings from the key informant interviews, strengthening the validity of the thematic analysis through triangulation of methods (e.g. in-depth individual interview versus group discussion) [14, 15].

Results

A total of 13 interviews were conducted; the interviewees comprised 5 managers, 3 medical officers, 2 directors, 1 advisor, 1 scientist and 1 biostatistician; 6 of the interviewees were from Toronto Public Health, 4 from Public Health Ontario and 3 from Ontario Health. The mean duration of interviews was 51 minutes (standard deviation: 9.8 minutes). The pair-wise inter-coder reliability was 77%, 79% and 87%. After coding the transcripts, the following themes emerged, which we present as barriers (figure 1A) and enablers (figure 1B).

Figure 1: Themes following key informant interviews. Themes were categorised as barriers (A) and enablers (B). Lines connect themes believed to be directly interconnected.



Barriers to advancing AI/ML in public sector health organisations

Education and expertise [Phase of Maturity: exploring or experimenting; appendices 3–4]

One barrier is insufficient knowledge, skills, expertise and experience with AI/ML. AI/ML was not featured in the formal training of the existing workforce, and interviewees felt that they do not have the required knowledge to lead an AI initiative without further training. This includes the technical skillset needed for effectively using R and Python for AI/ML, analytics programs recently embraced by public health agencies.

"I'm in the process of learning it [Python] truthfully at the moment thinking that it's a requirement for future work with AI." – [Advisor]

Owing to competing priorities and current job demands, there is a perception that there is little time to devote to learning what is perceived as a new field of study (AI), understanding the complexities of building and communicating machine-learning models, and learning unfamiliar syntax (R and Python).

"Data literacy and knowledge of what these terms actually mean in application to our work takes a significant amount of effort." – [Director]

"I think all of us early adopters are starting to form our own little group at work and we're connecting. But I think there's a huge swathe of people within the organisation who don't understand what all this is." – [Associate Medical Officer of Health]

Competing priorities [Phase of Maturity: exploring on the Governance dimension]

There are additional competing priorities that serve as barriers to advancing AI/ML in the public health sector. Even in January to May 2024, public health organisations are re-focusing their efforts on restarting work that was put on hold during the COVID-19 pandemic with little bandwidth to start new projects:

"You know, we've been so, you know, heads-down focused in on the pandemic, which coincided with this rapid explosion of AI that, you know, our focus has been recovering from the pandemic and getting our programs running." – [Manager]

Moreover, people are aware that significant financial investment (time and people) would be required to do things properly and avoid the risk of reputational harm:

"If you don't do it right the first time, that perception, it's kind of difficult to erase, right?" – [Manager]

Technology and computing infrastructure [Phase of Maturity: exploring or experimenting in the Technology dimension]

Interviewees shared the sentiment that machine-learning methods require significant amounts of data and computational resources. However, additional education and training would be important to ascertain whether these barriers are merely challenges or are truly insurmountable. For use cases that do require computational power beyond what is currently available, access to such resources may limit public sector health organisations depending on their level of computational maturity. Changing technology in a large organisational structure is difficult, costly and takes time.

"Our tech is archaic. We don't have the resources for the appropriate technology… I don't think we have enough staff who know how to code and use the technology." – [Associate Medical Officer of Health]

Financial barriers [Phase of Maturity: exploring and experimenting in the Technology and People dimensions]

Significant and sustained investment is needed to accomplish two complementary aims. The first is to augment the knowledge base of the workforce by hiring staff with the required skillsets (but who may lack subject-matter expertise) and upskill current staff who may have subject-matter and organisational expertise but lack the domain-specific knowledge.

"Even in terms of training people up to be able to do the work right, trying to get decision scientists and data scientists into the organisation, you're paying a premium for those types of analysts because their skills are in high demand." – [Manager]

The second is to modernise technology to ensure the right computational requirements and resources are available.

"Technology implementations are not cheap if you want to do them properly." – [Manager]

"Existing budgets don't have any space for new funding for AI technology." – [Manager]

Privacy, ethics and data security [Phase of Maturity: exploring and experimenting in the Technology, Data and People dimensions]

Public health organisations collect personal identifying information (PII) and personal health information (PHI) for the purposes of health system monitoring, health system planning and quality improvement. A lack of education and clarity around the terms "machine learning" and "artificial intelligence" can stoke fear from the perspectives of those whose role is to safeguard the privacy and security of the data. AI/ML can appear "too risky" to a public sector organisation that is culturally risk-averse.

"The culture in this area is pretty risk-averse… And no matter where you're coming from, these pieces of technology look risky." – [Associate Medical Officer of Health]

It is not always possible to completely anonymise or pseudonymise data for the needs of public sector health organisations. Examples include parsing through clinic notes (free text), transcribing data directly into the medical charts to reduce administrative burden on physicians, and case-contact management systems for infection control. There is uncertainty around the privacy, ethical and security concerns around cloud-based platforms that are managed by a third-party (external) agency.

"Perception that it is impossible… we still have a lot of people that think the cloud is not secure." – [Manager]

While there is recognition of the benefits to enable scale, there are data ownership concerns associated with the use of commercial AI platforms. In particular, a public sector health organisation can benefit from the use of a commercial AI platform, but peoples' health data are used to improve such platforms. The commercial entity recovers the financial rewards of such an improvement, but the data used for the improvement is not theirs.

"Whatever records that I would use to feed into AI need to lack PHI [personal health information]. And it also depends on agreements with AI vendors… so there's the legal aspects in terms of whether they retain the data, the data models, et cetera." – [Advisor]

Responsible use is also important. Unsupervised AI/ML models could miss important health issues, incorporate bias or can become less accurate over time. These effects can directly impact population health, necessitating validity checks and periodic re-assessment of accuracy.

"It needs to be done in a way that's transparent, ethical, accurate and is monitored over time to ensure that there's no bias in the process." – [Director]

"We can't go into the use of AI lightly, especially for something like Communicable Disease Control, where you're dealing with life and death." – [Manager]

Fear of people being replaced [Phase of Maturity: none identified]

Lastly, there was some acknowledgement that people may be afraid of losing their jobs, but the interviewees did not share this sentiment given their familiarity with the topic. Education is critical to help staff and leadership understand efficiencies that will be gained, including time that can be better spent elsewhere.

"We can dedicate people's time to better things." – [Director]

"I'm not trying to make everyone unemployed here, but I'm just saying there's a lot of solutions that could create a lot of efficiencies from the business perspective." – [Associate Medical Officer of Health]

"I don't think people are worried about losing their jobs, mostly because the way that these presentations are explained. It's not about replacing somebody, it's about augmenting them." – [Advisor]

Enablers to advancing AI/ML in public sector health organisations

Leadership [Phase of Maturity: exploring or experimenting in the Strategy dimension]

An organisational strategic plan that specifically mentions AI as a priority would enable it to move forward with the necessary financial support, governance system and encouragement from senior-level champion(s). Developing and disseminating standards, best practices, and legislation governing this work would be valuable to ensure success.

"We need more support from people at a higher senior level to encourage or motivate or support us." – [Biostatistician]

"Needing to have structure/governance to enable this work to happen, including use cases/organisation priorities." – [Manager]

"Need to have the commitment from senior management to be willing to walk that road with you and making sure that you're choosing the right examples or the right proof-of-concepts or the right services." – [Manager]

Partnerships [Phase of Maturity: exploring and experimenting in the Technology and People dimensions]

Creating partnerships with other public sector organisations and academic organisations with expertise in AI was seen as important for success. Other public sector organisations (not necessarily specific to health) have already implemented an AI/ML solution that others may benefit from or learn from. For select applications that focus on uncommon events of public health importance (e.g. measles infection, mpox infection), pooling data across multiple jurisdictions will enable more robust models for training and testing that can benefit all partners.

"The tools require a lot of data to train to get them better… so we need to collaborate across the province or even across the country." – [Associate Medical Officer of Health]

Partnerships with academic organisations that have the expertise but not the data or the policy context creates another win-win scenario: public sector health organisations will gain experience and computational proficiency to accomplish their goal, while academicians will have the opportunity to develop their methods further to meet the real-world use cases.

"There is a gap between academia and public health." – [Scientist]

"We need to partner together instead of going it alone." – [Manager]

Use cases [Phase of Maturity: exploring or experimenting in the Strategy dimension]

In order to demonstrate the benefit of AI to leadership, successful applications are needed. At the organisational level, gains in efficiency (e.g. freeing up human resources for other important tasks) demonstrate a return on investment, which in turn can fuel further investment. At the population level, success can manifest through better access to information and services to provide the right care when and where it is needed, and lower waiting times for receiving care (e.g. centralised referral systems; higher patient-physician throughput by reducing the administrative burden on physicians). Use cases that arose tended to focus on increasing efficiency of the health system:

"I sometimes feel like they don't get our day-to-day, and just even advocating for things like AI scribes would literally save hundreds and thousands of person-hours, which we can then invest those human hours into, like connecting with the community and preventing illness." – [Associate Medical Officer of Health]

"It reduces our use of human resources in low-valued work like answering the phone… Wouldn't it be great to automate that so that we can use our human resources in areas that are more valued?" – [Associate Medical Officer of Health]

Initial or first use cases are preferably simple so they can be explained to a broad audience and quickly gain confidence and buy-in. Interviewees acknowledged that we don't need to implement a full solution for a proof-of-concept type project.

"Getting some support to prioritise which use cases have the most impact." – [Manager]

"Making sure that you're choosing the right examples or the right proof-of-concepts or the right services." – [Manager]

Tabletop discussions: how to build data science functionality in public sector organisations

This section describes the in-person debriefing exercise to reflect on the findings and discuss specific questions related to themes culminating from the key-informant interviews.

Where do you see the biggest potential for data science applications in your organisations?

One point raised was gaining efficiency from day-to-day tasks or tasks deemed time-consuming and repetitive. General examples include using AI to write code or screen the literature (with or without information extraction) on a specific topic.

Building on what you heard, what are the main obstacles to achieving data science functionality in your organisations / in the public sector?

One obstacle was the fact that AI/ML is still in its infancy from the perspective of public sector health organisations. Those select early innovators are pioneering a few applications, and existing leadership is not knowledgeable enough to fully be able to set a strategy that considers the risks and benefits. Importantly, there is still a lack of clarity on why AI/ML is needed.

What are creative ways we can overcome these barriers?

One issue that was raised was the limited quality of the data that are ultimately used to build AI models. One solution was to use AI to improve the quality of the digitisation of health information at the source (e.g. primary care at the point of care/access). Investing in AI infrastructure and training at those sources may have the most impactful downstream effects.

Privacy has come up a lot as a barrier; how do we move past this?

There was a call to make data more accessible, and a centralised point of access to data has been suggested. Distrust in cloud-based tools was stated as a concern, and one potential solution was to gain a more thorough understanding of the security features that cloud-based tools offer.

Who do we partner with outside the public sector to enable data science? How do we govern these partnerships?

Creating and maintaining partnerships outside the public sector was seen as valuable, but there is a lot of uncertainty because of privacy, governance and organisational policy issues. It is also difficult to govern policy on AI given the frequent changes and variable regulatory environment.

Data science infrastructure will take investment, partnership and accountability – who do you see taking on these roles?

Without standards, people may feel uncomfortable advancing AI/ML in their organisation. Canada's Artificial Intelligence and Data Act (AIDA) and Bill 194 "Strengthening Cyber Security and Building Trust in the Public Sector Act, 2024", while not specific to the healthcare industry, is a good start to providing a foundational policy and regulatory context [16, 17]. Learning from other jurisdictions that may be further along the process of AI/ML adoption and understanding the strengths and limitations of AI/ML are important to govern its appropriate use.

Discussion

Following key informant interviews at three public sector health organisations and a tabletop exercise at an open workshop, we find that health organisations within Ontario's public sector are "relatively inexperienced" in AI/ML, dependent on motivated staff to take the lead on projects and engage external partners [18].

We identified several barriers and enablers for using AI/ML. These findings align with some of the priorities identified from literature reviews, including data governance; analytic infrastructure; workforce knowledge and skills gap; development of strategic collaborative partnerships; and embracing AI as a tool [18–20]. Although the purpose of this study was not to establish the state of AI Maturity in public sector health organisations, the comments from the key informant interviews suggest that these organisations are either in the exploration/ad hoc phase (e.g. the organisation is learning about AI) or experimentation phase (e.g. assessing proof-of-concepts) of AI maturity [12, 13]. Element AI's AI Maturity survey was administered to a range of organisations in 2019–2020

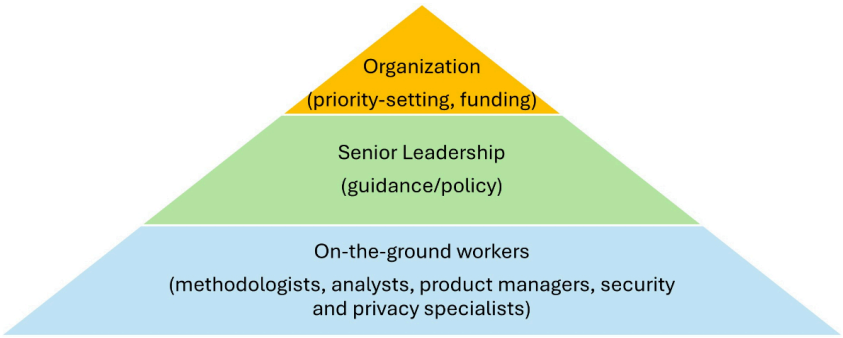
[12]. Although focused on the private sector, results are similar to ours with most organisations in the exploration and experimentation phases. The most advanced sector was health, pharma and biotechnology companies, in which 20% of companies reported operating in the formalising (20%), optimising (7%) or transforming phases (7%) [12]. Although a survey of public sector organisations was not reported, our key informant interview responses also align with organisations predominantly in the exploration/ad hoc (phase I), experimentation (phase II), and planning and deployment (phase III) stages of maturity.

AI/ML as an innovation

To advance AI/ML in the public sector, changes must be made at multiple levels within an organisation, enabled by project management, change management, publication of policies/guidelines and knowledge translation. As a starting point, many organisations working with PHI have begun to adopt analytic programs and reorganise their information technology infrastructure to support AI/ML. Part of the change management process involves giving people time to react and dispelling myths or misconceptions. For example, respondents shared fears about the security of cloud computing, yet most major data organisations are moving their data (or already have) to a cloud provider. This is essential for enabling advanced analytics (e.g. large language models) and growing costs associated with maintaining ever-increasing data repositories [21–23].

Decisions are made by senior leadership but require organisation-wide restructuring to allow product managers, security specialists and privacy experts to ensure work with PHI is appropriate (figure 2). Moreover, the transition directly affects on-the-ground workers tasked with implantation and use, requiring persistent messaging and support for successful change management [18].

Figure 2: Organisational changes required to enable AI/ML.



Greenhalgh et al. developed a conceptual model for considering the determinants of diffusion (passive spread), dissemination (active and planned efforts for adoption) and implementation (active and planned efforts to convert an innovation into mainstream) of innovations in public sector health organisations [24]. There are many forces influencing whether (and how) an innovation like AI/ML will pervade the public healthcare system, including features of the innovation itself, communication and influence of the people within the organisation, system antecedents, system readiness for innovation, adoption/assimilation and the implementation process [24]. Previous work on performance measurement speaks to the importance of leadership (e.g. formalised prioritisation) and organisational commitment (e.g. dedicated funding) in performance improvement, factors identified by our study as key enablers [25].

Risks and biases

The rate at which AI/ML is advancing continues to outpace that of regulation, opening the door for harms that can affect peoples' lives, jeopardise the reputation of an organisation and thwart potential gains that can otherwise be achieved by using AI/ML [26]. For example, the chatbot Tessa that was meant to serve as a human-free eating disorder hotline was discontinued after giving people bad advice [27]. As another example, racial biases have been recognised as a risk to any predictive model, but is further complicated in the context of AI/ML because even in scenarios when ra-

cial data are invisible to the algorithm, algorithms may still not be free of biases [28–30]. Being aware of such biases is important but not always obvious when they occur through unknown or unpredictable mechanisms [28, 31, 32]. Interviewees did not consistently identify bias as a risk for AI/ML, nor did they mention Indigenous data sovereignty or public trust as barriers, suggesting that these areas are not yet fully appreciated. Because public sector health organisations often access and use sensitive and identifiable information on the population they serve, care must be taken to ensure the potential impact of AI on equity is explored and understood, and protected data (e.g. Indigenous identity) are not incidentally unmasked. Transparency and methodological rigour are needed to promote public trust in AI applications, particularly when the methods are not always explainable [33–35]. On 1 December 2024, the Government of Ontario issued the Responsible Use of Artificial Intelligence Directive, which applies to all publicly funded agencies in the province [36]. This directive requires all agencies to create a policy around the use of AI, which includes activities related to ensuring transparent, responsible and accountable use of AI.

A way forward

From these experiences and the results from the key informant interviews and tabletop discussions, we recommend small-scale use cases that can be used as proof-of-concept with rigorous pilot testing to ensure we understand the risks and limitations before widespread implementation in public sector health organisations. These findings align with recommendations following a survey of eight Swiss public organisations also in an early stage of AI maturity [18]. Another useful construct is to consider formal partnerships and exchanges across policy and academia that can serve to address many of the technical and expertise challenges while ensuring the health and policy relevance.

Strengths

One of the strengths of this study is the interpretation of the findings in conjunction with existing frameworks. Public sector organisations can directly apply these findings to target specific aspects of their organisational structure, culture and workforce to align with their strategic goals around AI use. For a publicly funded system, efficient and appropriate use of resources is critical to ensure that any investments into AI yield a return, either through improved efficiency, cost savings, or cost-effectiveness, while maintaining fairness, transparency, human resources, and encouraging public trust.

Limitations

One limitation of the present study is the potential for interviewer biases to overshadow some of the themes that may have been present in the data. However, this may be acknowledged as a fundamental aspect of post-positivist qualitative research that is better to be acknowledged than dismissed [7, 9, 37]. Another limitation is the potential for AI to quickly render some of the themes or comments obsolete. For example, readily accessible large language models having human-like performance for coding in an array of programmatic languages may remove this component as a barrier to AI/ML implementation [38]. Another limitation is the AI environment is changing rapidly. Since the time the interviews were conducted and the time of reading, many of the elements and sub-elements of either AI Maturity Framework examined may have advanced. With the governmental AI Directive in place, all public organisations are mandated to develop their AI policies, which includes AI and data governance, assessing data readiness for AI and educating staff on the risks and policies around AI usage. Formal assessments of AI Maturity are warranted, and these should be repeated more frequently to reflect the pace of AI development and accessibility.

Transferability

We believe our results are transferrable to industries beyond healthcare that are in a similar state of maturity around AI/ML adoption [39]. Although industry-specific challenges and use cases may arise, the same barriers and enablers would be relevant to applications of AI/ML. Examples include areas such as education where teachers are seeking to leverage AI to assist with day-to-day tasks like scheduling and planning [40]. An interview hosted by Ontario's Information and Privacy Commissioner's office on the use of technology in the classroom illustrates the risks around privacy and exploitation of public dollars by "persuasive technology" from third-party vendors integrating their AI products into existing infrastructure [40]. Many of these issues have direct corollaries to public sector health organisations, with AI Scribes being one prominent example and AI-enabled

electronic medical records being another [41]. The AI strategy for Canada's Federal Public Service 2025–2027, which is not specific to the health sector, has identified three of four sector-agnostic priorities with commonalities with our findings: 1) central AI capacity (e.g. identifying use cases, assessing risk); 2) policy, legislation and governance relevant to the AI era; and 3) talent and training [42].

Conclusion

Various barriers to AI implementation in public sector health organisations exist, including 1) knowledge, education and expertise; 2) privacy, ethics and security; 3) technology and infrastructure; 4) financial barriers; 5) competing priorities; and 6) fear of being replaced. Key enablers include 1) partnerships; 2) buy-in and support from senior leadership; 3) management and operational supports; and 4) actionable use cases. Demonstrating success from a few small-scale applications is important to identify risks and opportunities for improvement, but it is also important to share knowledge, experiences, and measure success for the perspectives of different partners within and across different organisations. Partnerships between academic and policy organisations provide one way to overcome limitations raised.

Data sharing statement

Even with redaction, transcripts can potentially identify the interviewee. Participants therefore did not consent to publishing their transcripts but agreed that representative and de-identified quotes can be published for the purpose of the article.

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Potential competing interests

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Appendix 1: Data science applications in public health sector organizations – Key Informant Interview guide

Preamble to be read verbatim:

Thank you for agreeing to be a key informant on this project related to the use of data science and AI in public health. The goal of this research is to understand the landscape of artificial intelligence (AI) in the public health sector. We seek to answer the questions about whether AI is used, how it is used, and how it could be used. This information will help inform a curriculum on AI for public sector health organizations, as well as a toolkit to help support the implementation of AI projects.

Before we start, I would like to confirm a few points:

- Have you reviewed the information sheet and consent form?
- Do you have any questions about the interview?
- I am confirming that confirm that they are content with the interview being recorded?
- From your consent form, you stated that you agree to being audio recorded and transcribed. Is that still the case?
- Can I confirm that I can email you your signed consent form?

Definition of key terms

During the interview, I will be using the terms "Data Science" and "Artificial intelligence or (AI)" For the purpose of our interview I will provide you the definitions of those terms [Say aloud and also place them in the chat].

Data Science combines domain expertise, programming, and statistics to uncover patterns in data using data visualization, statistical modelling, machine learning, artificial intelligence, spatial analysis, and other methods. In healthcare, we use data science techniques to discover trends and associations in order to guide decision- and policymaking to advance health and well-being using a data-driven process.

Artificial intelligence (AI) more specifically is an area of study traditionally within the field of computer science dedicated to solving problems commonly associated with human intelligence, such as learning, problem solving, visual perception, and speech and pattern recognition. AI in public health is the application of these techniques to improve disease surveillance, diagnosis, treatment personalization, resource allocation, and healthcare policy.

Key Informant Interview Questions

Part I: Current state / Background

Question	Prompts / comments for interviewers
1) Please describe your role and job title	- Access to data? - Manage data analysts?
2) Please provide a general overview of the type of data-focused work your department/program or team does at your organization	- let them know In the second part of the interview we will get into specifics on projects we can detail for case studies/use cases - Distinguish between regular vs occasional work
3) What types of data do you work with? (e.g.	- Are different data types used in the same

surveys, admin datasets, images, electronic health records, qualitative, documents, code, etc)	analytic tasks? - Structured vs unstructured data
4) What software (e.g. SAS, R, Python, Excel) and computational platform (e.g. laptop, server, cloud) do you use for data analyses?	- Are different programs used for the same analytic tasks?
5) What statistical or analytic software or tools do you typically use when you work with data? This can include descriptive statistics, regression-based methods, machine learning methods, or any other analytical method	

Part II: Possible uses of AI and barriers

Question	Prompts / comments for interviewers
6) Can you identify ways you can use data to improve the efficiency or effectiveness of your work?	-
7) Is there any potential for automation?	- Thinking of a few specific tasks, how would you rate your desire for automation to be? For example, completely automated (hands-off) or some oversight (human in-the-loop)?
8) What are the barriers of using AI/ML in your work?	- No use-cases have been identified - concerns/fears about AI - lack of knowledge/training - lack of technical / infrastructure - What data do you need that you currently don't have access to? - Are there any software/platforms you need that are currently unavailable at your organization?
9) What would make AI more feasible/likely?	- Third-part verification of AI tools (e.g. security, reliability) - Regulation coming from the organization

Part III: Completed or ongoing case studies

These next series of questions are meant to gather information that we can use to generate a list of case studies highlighting the work you have already done as related to Artificial Intelligence.

Question	Prompts / comments for interviewers
10) Do you have a specific example of a project you have worked on at this organization that used data science or AI techniques?	- If no, move to part IV
11) Can you briefly describe this work?	- share with us a paper or report that describes this work
12) What was the rationale for undertaking this project?	-
13) What types of data did you use for this project?	-
14) What analysis techniques did you use for this project?	- What makes you classify this as an AI use-case? - Why did you use advanced analytic techniques instead of simpler more traditional methods?
15) What challenges did you encounter during this project in terms of working within the constraints of your organization?	- Did any ethical or privacy issues related to the use of data science or AI come up during the project? - Is your data science or AI work dependent on the IT infrastructure/computing power at your organization? If yes, please describe how. - Are there any other limitations or barriers faced by your team(s) to perform this type of work?
16) Are there other organizations you are collaborating with to complete these projects?	- Why collaborate (business or pleasure)
17) Were there any barriers to conveying the results to key stakeholders?	-
18) What was the impact (or potential impact) of this project in terms of public health / health system policy making?	-

Part IV: Proposed case studies

These next series of questions are meant to gather information that we can use to generate a list of case studies highlighting potential use-cases for AI. These examples may be shared publicly.

Question	Prompts / comments for interviewers
1) Do you have a specific example of a project you would like to work on at this organization that would use data science or AI techniques for the analysis of data?	If no, probe whether: - No need - Unsure of need And end interview here
2) For one of these, can you describe that project?	As specific an example as possible
3) What would be the rationale for undertaking this project?	
4) What data would you use for this project?	
5) What analysis techniques would you use for this project?	
6) Are there any ethical or privacy issues related to the use of data science or AI that you anticipate would come up during the project?	
7) What challenges do you anticipate encountering during this project in terms of working within the constraints of your organization?	
8) What would be the impact (or potential impact) of this project in terms of public health / health system policy making?	
9) Why would you use advanced analytic techniques instead of simpler more traditional methods?	

Appendix 2: Standards for Reporting Qualitative Research (SRQR)[1]

Title and abstract			
S1	Title	Concise description of the nature and topic of the study Identifying the study as qualitative or indicating the approach (e.g., ethnography, grounded theory) or data collection methods (e.g., interview, focus group) is recommended	The title states that the work is qualitative in nature
S2	Abstract	Summary of key elements of the study using the abstract format of the intended publication; typically includes background, purpose, methods, results, and conclusions	Included in the abstract
Introduction			
S3	Problem formulation	Description and significance of the problem/phenomenon studied; review of relevant theory and empirical work; problem statement	Described in the introduction
S4	Purpose or research question	Purpose of the study and specific objectives or questions	Included at the end of the introduction
Methods			
S5	Qualitative approach and research paradigm	Qualitative approach (e.g., ethnography, grounded theory, case study, phenomenology, narrative research) and guiding theory if appropriate; identifying the research paradigm (e.g., postpositivist, constructivist/ interpretivist) is also recommended; rationale[2]	Qualitative approach: case studies (interviews) Research paradigm: postpositivist
S6	Researcher characteristics and reflexivity	Researchers' characteristics that may influence the research, including personal attributes, qualifications/experience, relationship with	Stated in the methods, "Key informants were identified *a priori* by interviewers based on institutional knowledge of who would be good candidates as key opinion leaders on

		participants, assumptions, and/or presuppositions; potential or actual interaction between researchers' characteristics and the research questions, approach, methods, results, and/or transferability	the topic of AI/ML in their respective organizations." Researchers had at least a professional relationship with some of the interviewees. This was important to be able to identify suitable candidates to interview for this study, but also to understand the often-nuanced culture within organizations. It is unclear how this may influence the research.
S7	Context	Setting/site and salient contextual factors; rationale[2]	The setting is described in the methods
S8	Sampling strategy	How and why research participants, documents, or events were selected; criteria for deciding when no further sampling was necessary (e.g., sampling saturation); rationale[2]	- Participant sampling is described in the methods. Interviewers identified peers through institutional knowledge, and through a snowballing approach, interviewees were asked to identify additional candidates who may have different experiences to share. - Saturation of responses was determined subjectively, while considering the time investments required to conduct further interviews
S9	Ethical issues pertaining to human subjects	Documentation of approval by an appropriate ethics review board and participant consent, or explanation for lack thereof; other confidentiality and data security issues	Research Ethics Board approval and participant consent were obtained.
S10	Data collection methods	Types of data collected; details of data collection procedures including (as appropriate) start and stop dates of data collection and analysis, iterative process, triangulation of sources/methods, and modification	- Dates of interviews: January to March 2024 - Date of in-person workshop (triangulation of methods): May 2024 - Procedures were not modified

		of procedures in response to evolving study findings; rationale[2]	throughout the course of the study
S11	Data collection instruments and technologies	Description of instruments (e.g., interview guides, questionnaires) and devices (e.g., audio recorders) used for data collection; if/how the instrument(s) changed over the course of the study	- Interview guide in Appendix 1 - Microsoft Teams, as described in the methods - The instrument did not change over the course of the study, but we note a global Microsoft Teams outage on January 26, 2024 that affected the recording, but not the transcription
S12	Units of study	Number and relevant characteristics of participants, documents, or events included in the study; level of participation (could be reported in results)	- 13 interviews - Relevant participant characteristics were described (e.g., title, organization)
S13	Data processing	Methods for processing data prior to and during analysis, including transcription, data entry, data management and security, verification of data integrity, data coding, and anonymization/deidentification of excerpts	- Transcription done through Microsoft Teams - Data cleaning includes correcting the transcription when necessary by listening to the audio recording - Audio and transcriptions were de-identified (names changed to a randomly study ID) and stored on a secure server. Only the researchers have access
S14	Data analysis	Process by which inferences, themes, etc., were identified and developed, including the researchers involved in data analysis; usually references a specific paradigm or approach; rationale[2]	- Researchers coded the text individually - Codes were compiled into themes based on their perceived commonalities, organizational hierarchies, and pragmatism - The researchers were involved in all steps of the process (interviewing, coding, and thematic analysis)
S15	Techniques to enhance trustworthiness	Techniques to enhance trustworthiness and credibility of data analysis (e.g., member checking, audit trail, triangulation); rationale[2]	- Triangulation of methods increased the credibility of the research - Credibility is further supported by including key opinion leaders at

			each organization
Results/findings			
S16	Synthesis and interpretation	Main findings (e.g., interpretations, inferences, and themes); might include development of a theory or model, or integration with prior research or theory	- 6 barriers and 4 enablers (themes) were described
S17	Links to empirical data	Evidence (e.g., quotes, field notes, text excerpts, photographs) to substantiate analytic findings	- Representative quotes were provided, along with the title (e.g., “manager”) of the speaker
Discussion			
S18	Integration with prior work, implications, transferability, and contribution(s) to the field	Short summary of main findings; explanation of how findings and conclusions connect to, support, elaborate on, or challenge conclusions of earlier scholarship; discussion of scope of application/ generalizability; identification of unique contribution(s) to scholarship in a discipline or field	- Transferability is discussed. We believe that the results are transferrable to other public health industries beyond healthcare. Although evidence is sparse, we find strong similarities between what has been expressed in the publicly funded education system in Ontario
S19	Limitations	Trustworthiness and limitations of findings	- A limitations section was added to discuss the trustworthiness and limitations.
Other			
S20	Conflicts of interest	Potential sources of influence or perceived influence on study conduct and conclusions; how these were managed	- No conflicts of interest were identified. There was no relationship between interviewer and interviewee where there was a unilateral source of power dynamic.
	Funding	Sources of funding and other support; role of funders in data collection, interpretation, and reporting	- No specific sources of funding were used for this research

[1] the SRQR was obtained from O'Brien BC, Harris IB, Beckman TJ, Reed DA, Cook DA. Standards for reporting qualitative research: a synthesis of recommendations. *Acad Med*. 2014;89(9):1245-1251.

[2] The rationale should briefly discuss the justification for choosing that theory, approach, method, or technique rather than other options available, the assumptions and limitations implicit in those choices, and how those choices influence study conclusions and transferability. As appropriate, the rationale for several items might be discussed together.

Appendix 3: AI Maturity Framework [a]

	Stage of Maturity [b]	
Dimension of Enterprise AI	**1. Exploring**	**2. Experimenting**
Strategy (Organizational vision and roadmap to sustain forward momentum for AI)	- Individual groups are studying use-cases	- No overarching strategy or vision for AI yet - Advancing proof-of-concept (POCs) use-cases - Limited funding exists for POCs, supported by senior leadership
Data (Powering AI models from training to production)	- Leaders do not have a good sense of what unstructured data sources could be available for AI - Special expertise is needed to understand the data - Specialised tools for data preparation, such as for data labelling, are not yet available	- Some teams have been able to collate the data for AI use-cases
Technology (Tools, infrastructure and workflows for powering AI across the solution lifecycle)	- Specialized AI/ML solutions not in place - Business leaders are unsure of what's needed - Modeling is done on personal computers	- Using cloud-based infrastructure to leverage GPU power beyond personal machines
People (Roles, skills and measures of success to work smarter with AI)	- The organization hasn't defined roles and responsibilities for AI and doesn't yet know how to do so	- Typically, small teams with internal experts in data science, business intelligence (BI) or advanced analytics start experimenting with Proofs of Concept (POCs) - Recognition of informal efforts to provide skills and resources for new roles exists, leaning towards the next stage of maturity (formalizing)
Governance (Policies, processes, and structures to ensure responsible and safe AI)	- Board members, management teams and employees are beginning to educate themselves about responsible AI so they understand new or heightened risks, obligations, and opportunities	-

[a] Adapted from Ramakrishnan K, Abuhamad G, Chantry C, Diamond SP, Donelson P, Ebert L, et al. The AI Maturity Framework: A strategic guide to operationalize and scale enterprise AI solutions [Internet]. Element AI; 2020 (https://s3.amazonaws.com/external_clips/3430107/AI-Maturity-Framework_White-Paper_EN.pdf).

[b] The remaining three levels of maturity (3. Formalizing; 4. Optimizing; and 5. Transforming) have not yet been reached

Appendix 4: IBM's AI Maturity Model[1]

	Technical elements			Organizational elements		
	Big Data	**Computational systems**	**Analytical capacity**	**Innovative climate**	**Governance and ethical frameworks**	**Strategic visioning**
Ad hoc	- Data governance frameworks are constructed around experimental projects	- Required AI systems are not present - AI systems have limited capacity to ingest and analyze large-scale data -	- AI developers, data scientists, and other analytical resources learn by self-teaching or are hobbyist	- Individuals are left to their own to experiment with AI - No policies in place to recruit, develop, and retain talent needed to develop and manage AI systems	- No formal governance and policy frameworks to guide AI - No ethical framework to guide design, development, and deployment of AI - No accountability for AI	- AI projects are not part of the strategic agenda of the agency
Experimentation		- Initial prototypes of AI are developed and/or acquired but are still primarily under the radar and are one off systems - AI systems are focused on analyzing past data and building associations between elements of interest (i .e ., descriptive analysis)	- Initial efforts are conducted to assess analytical capacity within the agency - Analytical capacity is centered around pilot projects - Initial efforts are commissioned for staff to receiving training to bolster their analytical capacity	- Agency supports innovation on AI within controlled settings - Risk continues to be the most significant factor that dominates AI adoption and use decisions - Within pilot projects, focus is on addressing low hanging fruit type efforts where risk is low and results can be easily demonstrated		- Senior leadership is aware of AI pilot projects but are generally hands-off - Limited one-off funding is provided for pilot projects
Planning and deployment		- AI systems are purchased and or licensed by		- Support is provided for innovation in a		- Senior leadership is aware of AI

		departments and/or teams within the agency		few targeted areas on AI		efforts and are generally supportive of the initial projects - Funding is provided for planning and initial deployments for AI - Early mentions of AI in key strategy documents appear but lack sufficient detail

1. Artificial Intelligence in the Public Sector: A Maturity Model | IBM Center for The Business of Government. https://www.businessofgovernment.org/report/artificial-intelligence-public-sector-maturity-model. Accessed October 22, 2025.